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MODELLING THE LIFETIME EMPLOYMENT PATTERNS OF CANADIANS

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No. 4

Statistics Canada
Analytical Studies Branch

Research Paper Series

Canada

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Social and Economic Studies Division
Statistics Canada
Winter 1986

ABSTRACT

This paper utilizes data from Statistics Canada's Family History Survey (FHS) to study the relationship between family-related variables and the movement of Canadians - women in particular - in and out of employment. These relationships are explored by expressing transition probabilities as a function of variables such as age, sex, marital status, age of youngest child and educational attainment. The transition probabilities are also conditioned upon the state occupied the previous year, and the duration in that state. The goal is to develop an employment submodel of a larger Lifetime Income and Pension Policy Simulation Model (LIPPS). The simulated employment patterns are compared to the actuals from the FHS.

ACKNOWLEDGMENTS

The author wishes to thank Ted Wannell for his assistance throughout this project, and Paul Shaw for his suggestions early in the project.

Key Words: simulation model, transition probability, labour force participation, employment, longitudinal.

Introduction

This paper utilizes data from Statistics Canada's Family History survey to model the movement of men and women into and out of employment during their lifetime. Emphasis is placed on modelling the employment transitions of women as a function of their personal characteristics, family-related variables, and past employment history. The overall objective relates to the need to develop an employment submodel for a larger Lifetime Income and Pension Policy Simulation (LIPPS) model being developed in the Social and Economic Studies Division of Statistics Canada. The pattern of employment of individuals over their lifetime is important in assessing pension policy. In particular,the degree of continuity of employment, particularly among women, is of major importance since both the entitlement and size of the pension benefits depends upon whether women's employment patterns are sporadic or not. Thus, to the extent that it exists, it is important to capture the relationship between duration in the employment states, and the probability of being employed in any given year.

When cross-sectional data are used to model lifetime employment patterns, the participation in employment during a particular year is usually necessarily assumed to be independent of employment status in earlier years. This is because the data are usually not available to assess this relationship on cross-sectional data bases. If a strong dependence between past and current employment exists but is not captured in a model, the result is too many transitions between states, and a model which produces an employment pattern which is too sporadic.

Evidence would suggest that an individual's work behaviour is very much dependent upon their behaviour in earlier years. In their major work using Michigan Panel Study of Income Dynamics data, Nakamura and Nakamura (1985) noted that "the work behaviour of individuals seems to be characterized by considerable inertia". They found a tendency for the current years employment status to be strongly associated with the previous years status. The results of this work are discussed throughout this paper. Although longitudinal data do not exist in Canada as in the United States, Boothby (1984) used Survey of

Consumer Finance's data of Statistics Canada to assess the extent of continuity over time in married women's labour force attachment. He found "far more continuity in Canadian married women's labour force participation than cross-sectional models of participation would imply". He noted that "any attempts at prediction for policy purposes, such as simulating entitlements under the Canada pension plan, should take into account the existence of considerable continuity in married women's participation in the labour force".

American studies using panel data (eg. Heckman (1981) and Nakamura and Nakamura (1983)) have come to similar conclusions.

Other aspects of the probability of being employed besides work continuity are also addressed in this paper. The emphasis is on family-related variables (marital status, number of children and age) and other personal characteristics.

One of the major methodological issues addressed over the last few years by economists and econometricians has been related to alternative ways of estimating wage and labour supply functions that are free from the bias introduced by using data on working women only. This problem of using such data to determine the effect of wage levels on labour supply, and the sample selectivity bias which results from it, has been addressed by Heckman (1980), Goldberger (1981), Groneau (1974) and others.

One of the standard models of labour supply now typically includes three equations: one to estimate the probability of being employed, one to estimate hours of work, and one to estimate the wage rate. This standard model is discussed in Schultz (1980), Hanoch (1980), and Nakamura and Nakamura (1983, 1985). In this paper, it is this first step - estimating the probability of being employed in a given year - which is of interest. The probability of being employed - which is derived from the factors affecting offered and

reservation wages[1] - is seen to be a function of a number of types of variables: personal characteristics such as age and sex; human capital variables such as educational attainment and years of work experience; family characteristics such as marital status, number of pre-school aged children, the existence of a new born, and the event of a divorce; and macro economic variables such as the employment/population ratio. Perhaps most importantly, if the 'inertial' aspects of individuals work behavior is to be incorporated, such as in Nakamura and Nakamura (1985), variables reflecting the employment pattern in earlier years are necessary. Such variables are an important part of this work. Wage and income variables are often incorporated in models of labour force participation. The data base used in this study does not allow the inclusion of such variables. However, as is argued later in the paper, previous work suggests that when an individual's preference for work is captured through the "inertial" or state-dependence aspect of the model, the importance of directly measured wage variables as predictors of the probability of working decreases.

Data and Methodology

The Data

Data from the Family History Survey (FHS) of February, 1984 were used in this project. The FHS, a labour force survey supplement, was retrospective in nature and collected historical data on major family events such as marriages, child rearing, and work patterns. Persons 18 to 65 were surveyed, with a sample size of approximately 14,000.

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[1] In these models, an individual's decision as to whether to participate in employment is stated in terms of an "offered" wage and a "reservation" (or asking) wage. If the offered wage exceeds the reservation wage, the individual will enter employment. The probability of entering employment is modelled as the difference between the offered and reservation wage, or more specifically, as the probability that the offered wage will exceed the reservation wage. But the reservation wage cannot be measured or estimated directly. Both the offered and reservation wages are expressed in terms of other variables - personal characteristics, regional characteristics, other income, wage of spouse, etc. - which influence the offered and reservation wage. Thus, the model of the probability of entering employment - which is expressed as the difference between the expressions for the "offered" and "reservation" wage - has as the independent variables those which are seen to influence the reservation and offered wage.

Proxy responses[2], which are regularly used in the LFS, were not allowed, and hence individuals answered all questions pertaining to themselves. The work history data collected was minimal, probably because recall error becomes an important consideration when questions regarding labour market events of relatively short duration which occurred years earlier are asked. Regarding work history, the respondents were asked to recall the following information:

- the year in which first full-time or part-time job lasting 6 months or more was started (excluding part-time employment while at school)

- information on all work interruptions of one year or more, including, among other things, the year the interruption began and the number of years the interruption lasted.

From this information it was possible to determine for each individual when the "first entry" transition occurred, where first entry means entry into the first job lasting six months or more, and when other transition between the employment state (E) and the not employed state (NE) occurred. Only spells in NE lasting one year or more are included in the data. Hence, many transitions will be lost, since many men and women are unemployed for less than one year (the majority who are unemployed), and many women spend less than one year away from work following child birth. There may also be short spells in NE for other reasons. However, this is not of major concern here since for the LIPPS simulation model it is the number of <u>years</u> with no earnings which are important, and spells of less than one year out of employment would have little effect on the policy simulation results[3]. Furthermore, in the broader study of the labour force behavior of women in particular, it is the long spells of non-employment which are of concern, where skills may deteriorate, long-term day-care is required, homemaker pension provisions may be needed, etc.

Observations for all individuals on the file for the 10-year period 1974-1983 inclusive were used to estimate the models. This period was selected because to go back further would introduce more recall error.

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[2] Where questions are answered not by the individual whose labour force experience is being determined, but by another household member.

[3] Low income resulting from part-year employment are estimated in the income sub-model, which is a separate model. Here, it is necessary only to know if the individual was employed at any time during the year.

The Basic Regression Models

Different equations are estimated for individuals in the two states used in the model, employed (E) and not employed (NE). Note that employed means employed part-time or full-time at any time during the year. The transition probabilities, $Pr(NE_t \mid E_{t-1})$ and $Pr(E_t \mid NE_{t-1})$ are modelled separately. That is, the probability of leaving a state is made conditional upon the person being in the state the previous period. Of course, once the probability of leaving a state is known, the probability of staying is also.

The probability of leaving a state is seen to be dependent upon the duration in the state, which provides an indication of the individuals strength of attachment to the particular state. This is likely to influence the probability of leaving it. The models of the probability of changing states are estimated separately for males and females, and for the age groups 15-19, 20-39, 40-64, since the effects of the independent variables are likely to differ significantly among these groups.

The model for the probability of being employed is usually estimated using a non linear maximum likelihood technique such as Probit or Logistic regression[4] (as in Nakamura and Nakamura (1985), Hanoch (1980) or Schultz (1980)), although in earlier work the linear probability model using OLS was used (Bowen and Finnegan (1969)). In this particular work Logistic regression is used to estimate the probability of participation equation.

All equations take the following form:

$Pr(Y=1) = 1/(1 + e^{-(\alpha+Bx)})$ or, alternatively $\ln((Pr(Y=1)/(1-Pr(Y=1)) = \alpha + Bx$

[4] The Probit and Logistic regressions are very similar, and in practice provide similar results. The difference is that the underlying functional form of the model in Probit is a cumulative normal distribution, while in Logistic it is a logistic function. In practice, these functions are very similar except at the tails (see Amemiya, 1981). Since the dependent variable is dichotonous (employed or not employed), the Logistic and Probit techniques offer some advantages over OLS, notably: (1) OLS is not restricted to the 0,1 range, and probabilities outside this range may be estimated, while both Logistic and Probit analysis restrict probabilities to the 0,1 range, (2) there is a problem heteroscedasticity (non-uniform variances of the error term) when using OLS with dichotonous dependent variables.

where Y = 1 if transition is made
0 otherwise
X is a vector of independent variables
B is a vector of estimated coefficients
is the intercept term.

The Variables

The dependent variable is a dichotemous variable which takes the value 1 if a transition is made (either NE to E, or E to NE), 0 otherwise. The independent variables for which data were available from the Family History Survey and which are likely to influence the probability of individuals changing states are listed below.

The Independent Variables

1. Marital Status: married, not married (1 dummy variable)
2. Child Status: presence of newborn, age 1-5, age 6-16, no kids or kids 17 (3 dummy variables)
3. Educational Attainment: elementary, some secondary, completed secondary, completed postsecondary (3 dummy variables)
4. Ever-divorced Variable: (1 dummy variable)
5. Duration in the State (in years): in form of ln(DUR)
6. Employment/Population Ratio: in form of change in EMP/POP ratio between two years $[(EPR_t/EPR_{t-1}) - 1]$
7. Dummy age variables within the equations for broader age groups, e.g., Age 51-55, Age 56-60, Age 61-62, Age 63-64 in model for the 40-64 age group.

The First Entry to Employment

While in general the probabilities of exiting from a state are modelled as just described, there is one transition which is modelled separately - the probability of first entry into employment (i.e., the first NE to E transition). This is modelled separately because it is a unique transition unlike others, and also because the duration variable has a different meaning in this case. Before having been employed, duration in the NE state is perfectly correlated with age and is simply a reflection of years passed since some arbitrary starting point. The duration measure will vary, depending upon which arbitrary starting point is selected. However, once having been employed and then moved to the NE state, the duration measure is more truly a

reflection of time without a job having once been employed. Duration has a different meaning in the two cases, and a single duration variable could not be used to estimate a single $Pr(E_t \mid NE_{t-1})$ equation. Thus, it was necessary to model this transition separately.

Other Variables Commonly Included in the Model

There are other variables, notably wage and income related variables, which are often included in a model of participation in employment. They are not included here because the FHS does not contain the necessary data. Nakamura and Nakamura (1985) included the following variables in their model: lagged hours of work, lagged wage rates, levels of husband's income, and other family income. Of these, the most important appeared to be lagged hours of work. In this work, I have included the duration in the current state to capture the continuity in tendency to be employed between years. In the Nakamuras' work, other variables, such as the husband's income and "other income" variable seemed to have only a weak effect on the transition probabilities once the employment activity of the previous year was controlled for. It may be, as was speculated by the Nakamuras, that if one controls for the preferences of married women for home-oriented or work-oriented activities by controlling for the employment activity the previous years, as well as the length of time in the state - either employment or non-employment - then the observed relationship between husbands earnings and the labour supply of the wife may be quite weak.

Nakamura and Nakamura (1985) found a positive relationship between wages earned the previous period and the probability of remaining in employment (the lagged wage rate variable), but the effect was not strong, and was much less than for the lagged hours variable. Thus, of these variables the most important missing variable in a model formulated in this way appears to be the lagged hours of work. The duration variable replaces it in this model.

The Use of Pooled Data and Significance Tests

The dependent variable in all equations is the occurrence of a transition, and hence is dichotomous, taking on the value 1 when an out-of-state transition occurs, 0 otherwise.

Each individual can have up to 10 transitions over the period 1974-83, and hence each individual contributed 10 observations to the data set. The pooled data (over 10 years) are used because the exit transitions are relatively rare events in some demographic groups, and in many cases a single year's data would not provide enough transitions to reliably estimate the coefficients. This pooling of longitudinal data is often done, as in Nakamura and Nakamura (1985), and as described in Allison (1982). One problem arising from this approach is that the observations are no longer independent, a condition which is necessary if the statistical tests in the regression analysis are to be unbiased. Hence, the standard errors of the coefficients in the models are underestimated and the X^2 values in the tests of the null hypothesis for the coefficients are overestimated by some unknown amount. Thus, the X^2 tests associated with the coefficients should be viewed as descriptive statistics, not as good statistics for testing the null hypothesis. Following the approach used by Nakamura and Nakamura (1985), Cain (1966) and others, the significance of relationships is established more by showing that they can be replicated for more than one equation or demographic group, (i.e., across many of the 18 equations estimated) and that the effects of a variable are those that one would expect to observe given the current underlying theory. Perhaps just as important for the simulation model, another test of the significance of the estimated relationships is whether the simulated employment patterns produced using the model match the actual employment patterns. This test was done using a number of summary statistics. The results are reported later in the paper.

THE RESULTS

The results are presented for each set of independent variables (marital status, child status, etc.) in turn. Two pieces of information are used to indicate the observed effect between each independent variable and individuals employment patterns. They are: (1) the estimated regression coefficients from the logistic regression, and (2) estimated values (based on the regression equations) of the transition probabilities for selected hypothetical populations of interest.

The regression results for each of the 18 equations are shown in the tables on the following pages.

Table 1: LOGISTIC REGRESSION RESULTS MODELLING PROBABILITY OF FIRST ENTRY

$$\text{Model: } \ln \frac{P(y=1)}{1-P(y=1)} = \alpha + BX$$

$$\text{where } Y = \begin{cases} 1 & \text{if the individual entered a job lasting at least 6 months for the first time} \\ 0 & \text{otherwise} \end{cases}$$

Reference Group	Variable	Elementary or Some Secondary Education				Completed Secondary or Some Secondary				Postsecondary Graduates			
		Male		Female		Male		Female		Male		Female	
		Beta	x^2	Beta	x^2	Beta	x^2	Beta	x^2	Beta	x^2	Beta	x^2
	Intercept	-0.895	18.1	-1.443	43.8	-0.823	24.7	-0.171	1.4	-1.580	62.1	-1.626	68.9
Not Married	Married	0.516	4.6	-0.087	0.4	0.008	0.0	-0.518	7.8	0.351	2.2	-0.206	1.0
Kids > 6 or No Kids	Kid 0-5			-0.772	21.4			-0.794	17.1			-1.045	17.8
	EMP/POP*	2.423	0.7	2.37	4.3	1.629	0.5	1.893	4.1	6.796	5.6	2.775	5.0
	Age 17	-0.355	2.2	.099	0.2	-0.790	17.1	-2.012	103.4	-1.356	12.0	-1.914	26.7
Age 20	Age 18	0.000	0.0	.074	0.1	0.139	0.6	-0.463	8.0	0.041	0.0	-1.066	17.1
	Age 19	-0.260	1.0	-.006	0.0	0.179	0.9	-0.088	0.3	-0.203	0.6	-0.698	9.4
	Age 21 - 22	-0.193	0.5	-.052	0.4	0.167	0.6	-0.190	0.9	0.593	6.9	0.460	6.7
	Age 23 - 24	-0.261	0.6	-.357	1.3	-0.196	0.4	-0.539	3.4	1.040	18.5	1.082	26.8
	Age 25 - 26	-1.010	5.2	-.579	3.1	0.054	0.0	-0.773	4.9	1.034	11.8	0.805	2.5
	Age 27 - 30	-1.153	6.9	-.494	3.2	0.127	0.1	-0.726	5.8	1.037	7.5	0.423	1.8
	Age 31 - 40	-1.406	18.8	-1.197	21.0	0.817	1.2	-0.949	11.3	0.007	0.0	-0.009	0.0
Prop. of Pop. making transition		24.3		11.7		29.2		25.2		24.7		21.3	
Sample Size		1,292		3,148		1,927		2,954		1,375		1,944	
Model x^2		43.9		152.5		61.3		256.7		108.2		203.1	
p^2		.031		0.067		0.026		0.088		0.070		0.101	
d.f.		10		11		10		11		10		11	

$$\text{where } p^2 = 1 - \frac{\text{log likelihood for fitted model}}{\text{log likelihood for model with intercept only}}$$

* In form $(EPR_t/EPR_{t-1}) - 1$

Table 2: LOGISTIC REGRESSION RESULTS FOR 15-19 AGE GROUP

Reference Group	Variable	$PR(E_t \mid NE_{t-1})$ Male Beta	x^2	$PR(E_t \mid NE_{t-1})$ Female Beta	x^2	$PR(NE_t \mid E_{t-1})$ Male Beta	x^2	$PR(NE_t \mid E_{t-1})$ Female Beta	x^2
	Intercept	-0.713	3.4	-1.077	5.8	-3.101	333.2	-2.611	196.0
Not Married	Married			-1.251	3.3			0.712	4.9
No Kids	Kid 0-5			0.442	0.3			0.305	0.3
	Emp/Pop $\left(\frac{EPR_t}{EPR_{t-1}} - 1\right)$	-14.240	1.2	5.842	1.0	11.039	3.8	2.256	0.7
Sample Size		74		87		1,438		929	
Prop. of Pop. making transition		25.7		25.3		5.28		8.4	
Model	x^2	1.3		6.0		3.7		6.3	
	p^2	0.015		0.062		0.006		0.012	
	d.f.	1		3		1		3	

Table 3: LOGISTIC REGRESSION RESULTS FOR 20-39 AGE GROUP

Reference Group	Variable	PR (E_t | NE_{t-1}) Male Beta	x^2	PR (E_t | NE_{t-1}) Female Beta	x^2	PR (NE_t | E_{t-1}) Male Beta	x^2	PR (NE_t | E_{t-1}) Female Beta	x^2
	Intercept	-1.013	26.4	-0.910	40.5	-2.688	239.5	-1.968	319.7
Not Married	Married	0.074	0.2	-0.512	19.6	-0.435	15.6	0.541	49.7
No Kids	Kid 0			-0.716	28.6			0.512	29.8
	Kid 1-5			0.033	0.1			-0.566	30.9
	Kid 6-16			0.447	10.8			-0.770	57.7
	Elem.	-0.286	1.0	-0.688	15.9	0.193	1.3	0.319	6.1
Sec. Graduate	Some Sec.	0.009	0.0	-0.218	4.6	0.295	6.2	0.364	20.7
	Postsec. Grad.	0.896	21.8	0.351	13.2	-0.250	3.7	-0.096	1.6
No Failed Marr.	Failed Marr.			0.237	4.6			-0.183	4.8
	LN (DUR)	-0.870	51.6	-0.760	227.2	-0.581	69.1	-0.461	131.7
	EMP/POP*	0.465	0.0	1.478	3.1	-4.441	3.0	-2.66	16.7
	Age 20-24	0.070	0.1	-.066	0.3	0.157	1.4	0.022	0.1
Sample Size		1,116		8,261		23,341		15,091	
Prop. of Pop. making transition		22.3		9.3		2.0		7.9	
Model x^2		101.8		468.0		190.9		378.1	
p^2		0.086		0.092		0.043		0.045	
d.f.		7		11		7		11	

$$\text{where } p^2 = 1 - \frac{\text{log likelihood for fitted model}}{\text{log likelihood for model with intercept only}}$$

* in form $(EPR_t/EPR_{t-1}) - 1$

Table 4: LOGISTIC REGRESSION RESULTS FOR 40-64 AGE GROUP

Reference Group	Variable	$PR(E_t \mid NE_{t-1})$ Male Beta	x^2	$PR(E_t \mid NE_{t-1})$ Female Beta	x^2	$PR(NE_t \mid E_{t-1})$ Male Beta	x^2	$PR(NE_t \mid E_{t-1})$ Female Beta	x^2
	Intercept	-1.875	6.9	-1.311	20.1	-2.791	60.6	-2.852	192.0
Not Married	Married	0.521	0.8	-0.285	1.4	-0.560	13.2	0.275	4.1
40-50	Age 51-55	-0.038	0.0	-0.373	3.3	0.274	2.6	0.182	1.6
	Age 56-60	-1.033	3.0	-1.305	17.0	0.511	8.4	0.530	10.5
	Age 61-62	-8.773	-	-1.907	6.8	1.039	17.5	0.581	4.6
	Age 63-64	-8.899	-	-1.762	5.9	1.811	48.8	1.313	22.9
	Elem.	-0.151	0.1	-1.017	17.9	0.156	0.9	0.306	4.2
Sec. Grad.	Some Sec.	-0.941	1.7	-0.520	6.9	-0.120	0.4	0.144	1.0
	Postsec. Grad.	0.424	0.4	-0.037	0.0	-0.289	1.8	-0.117	0.5
	LN (DUR)	-1.243	17.9	-0.589	74.3	-0.419	17.5	-0.308	32.9
	EMP/POP*	31.341	2.4	2.042	0.6	-32.136	32.2	-7.244	16.3
	Sample Size	1,007		6,741		15,646		8,296	
	Prop. of Pop. making transition	2.7		2.7		1.8		4.5	
	Model x^2	59.0		155.5		152.4		106.1	
	p^2	0.238		0.094		0.054		0.035	
	d.f.	10		10		10		10	

* In form $((EPR_t/EPR_{t-1}) - 1$

Duration in the State

Duration in a state is often a good predictor of the probability of leaving it. In unemployment studies, for example, it is found that duration in the unemployment state is very significant in estimating escape probabilities (Hasen and De Brouker, 1985). Recently, work by Nakamura and Nakamura (1985), Boothby (1984), Heckman and Willis (1977), Heckman (1981) all indicate that the continuity of participation (or non-participation) is quite pronounced and must be captured in a model of labour force on employment behaviour. The forms of models used to assess the degree of continuity in these studies has varied considerably, but they all conclude that continuity in labour force participation (or employment) is important.

In this work, a fairly straightforward measure of continuity - the number of years in the state (employed or not-employed) is used as a measure of continuity.

There is some debate in the literature regarding "true duration" effects and heterogeneity and its effect on measured duration effects. In this paper there is no pretense of being able to separate these two possible sources of the effect of duration. Here, duration is seen as a predictor or measure of the strength of attachment to the state (whether employed or not employed). Duration is expected to be negatively correlated with the probability of leaving a state, and if such a correlation exists, then including the duration variable in the model will improve its predictive capability.

In the regression model, the duration variable was introduced in the natural log form.[5] This variable was dropped, however, from the 15-19 age group model since there is a lot of movement into and out of employment in this age group, usually after extremely short durations in employment. The coefficients did not appear significant for this population and hence were dropped.

Before examining the duration variable, the dependence between the probability of being employed and the state occupied the previous year is addres-

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[5] Dummy variables for four discrete ranges of duration (1, 2-4, 5-19, 10+) were also used, and the results were very similar.

sed. This gets at one aspect of the issue of continuity in the employment state.

To provide an indication of the model results, the values of the transition probabilities estimated by the models are calculated for a few hypothetical population groups, and reported in Table 5.

These results indicate that the probability of being in the employed state depends on which state the person occupied the previous year. For example, for married women aged 20-39, with no children and with completed secondary school, and employed the previous year, the probability of exiting is .20. Thus, the probability of remaining in employment is .80. But for the same population group, the probability of being employed if in the not-employed state the previous year is only .19. Thus, the state occupied the previous year is clearly important, as was found in Nakamura and Nakamura (1985). Cross-sectional models which did not account for the state occupied the previous year would over-estimate the likelihood of a transition between states. That is, the modelled employment pattern would be too sporadic.

However, these results suggest that not only does the transition probability depend upon the state the individual occupied the previous year, but also the length of time in the state.

The coefficients on the duration variable are large and negative in all age/sex group models (excluding the 15-19 group). Thus, the longer the duration in the state, the lower the probability of exiting from it). The values calculated in Table 5 indicate there is a significant decline in the probability of exiting from the state (employed or not employed) as duration in the state increases. The probability of exiting the state after 3 years duration are only from one-third to one-half as large as after one year.

Thus, for both men and women, the longer one is in the employed (or not-employed) state, the less likely the probability of exiting from it.

TABLE 5: Estimated Probability of Making of Transition, by Duration in the State
(Estimates Based on Logistic Regression)

Transition Type and Hypothetical Population Group	Duration in the State (years)						
	1	2	3	4	5	10	20
Prob. of Leaving Employment Given Have Been in E for x Yrs.* PR (E to NE | in E x Yrs)							
Males Age 20-39	.04	.03	.02	.01	0	-	-
40-50	.04	.03	.02	.01	.01	0	0
Females Age 20-39	.20	.15	.10	.05	.03	.01	-
40-50	.07	.06	.04	.03	.02	.01	0
Prob. of Re-entering Employment Given Have Been in NE for x Yrs.* PR (E to NE | in NE x Yrs.)							
Males Age 25-39	.25	.16	.07	.03	.01	-	-
40-50	.21	.10	.03	.01	.00	0	0
Females Age 25-39	.19	.12	.06	.02	.01	-	-
40-50	.17	.12	.07	.03	.01	-	-

* Other characteristics of this particular hypothetical group are: married, no children, no failed marriage and completed secondary school.

For many women who take work interruptions to raise children, this result may be counter-intuitive. It has often been considered that women leave employment to raise children, stay in the not-employed state for a number of years, and then returns. Thus, one would expect to see a high probability of exit from non-employment (i.e. re-entry to employment) after a few years, rather than after 1 or 2 years.

TABLE 6: The Length of Work Interruptions of Women

	The Proportion Re-entering Employment After							Total Number
	1 Year	2 Years	3 Years	4 Years	5 Years	6-9 Years	10+ or Never Re-entered	
Interruptions starting between 1973 and 1983								
All Interruptions*	20%	19%	7%	5%	5%	8%	34%	1 million
For "Pregnancy or Child Care" reasons	14%	18%	7%	6%	7%	10%	35%	0.4 mil.
Other reasons	24%	19%	7%	5%	4%	7%	33%	0.6 mil.
Interruptions starting between 1960 and 1969								
All Interruptions*	16%	11%	6%	5%	5%	13%	43%	1.0 mil.
For "Pregnancy or Child Care" reasons	14%	11%	7%	5%	6%	18%	40%	0.5 mil.
Other reasons	18%	12%	5%	5%	5%	8%	47%	0.5 mil.

* Lasting one year or longer. Those lasting less than one year were not captured in the sample.

Source: Family History Survey

However, data from the Family History Survey indicate that more women re-enter employment following the first year of a work interruption that at any other time. Furthermore, as time progresses, the proportion who re-enter declines (Table 6). This is true of work interruptions which started in the 1960s, as well as those starting in the 1970s. It is also true for women who took work interruptions for "pregnancy or child care reasons", as well as other reasons.

Not only is there a high degree of continuity in women's (and men's) employment status between years, but the strength of this continuity (i.e. the probability of remaining in a state) increases as the duration in the state increases.

Marital Status

It has long been recognized that labour force behaviour differs for married and unmarried women. Earlier researchers (Nakamura and Nakamura, 1985), having carried out analyses of changes in individuals labour market behavior as a result of changes in their marital status, suggest that these differences are likely due to the change in economic need and expectations concerning income flows from a husband, rather than any fixed, time-invariant set of preferences among women who tend to marry for home-oriented rather than market-oriented activities. The differences observed by earlier researchers also exist in the FHS data.

In the logistic regression, this is reflected in a higher probability of unmarried women first entering or re-entering employment, and a lower probability of leaving. These differences in the transition probabilities are shown in the coefficients of the logistic regressions and the estimated probabilities for selected hypothetical groups shown in Table 7.

The estimated probabilities suggest that married women are from 1.5 to 2 times more likely to leave employment and less likely to re-enter it than their non-married counterparts with other similar characteristics (age, child status, education, duration in the state). Unmarried women are also from 1.1 to 1.5 times more likely to enter a first job at a given age than their married counterparts with similar levels of education.

TABLE 7: Estimated Probability of Making a Transition, by Marital Status (Estimates Based on Logistic Regression Model)

Transition Type and Hypothetical Population Groups	Females		Males	
	Married	Not Married	Married	Not Married
Prob. of First Entering Employment Given Never Worked and Have Education Level Stated				
Hypothetical Population				
Elem. or Some Sec./Age 18*	.19	.21	.41	.29
Sec. School Grad./Age 18*	.24	.35	.34	.34
Postsec. Grad./Age 24*	.41	.46	.45	.37
Prob. of Leaving Employment Given Have Been in E State for 2 Years i.e., PR (E to NE | in E 2 Yrs.)				
Age 15-19**	.13	.07	.04	.05
Age 25-39**	.15	.09	.03	.04
Age 40-50	.06	.04	.03	.04
Prof. of Re-entering Employment Given Been in the NE State 2 Years i.e. PR (NE to E | in NE 2 Yrs.)				
Age 15-19**	.09	.25	.33	.33
Age 25-39**	.12	.19	.17	.17
Age 40-50	.12	.15	.10	.06

* Assumes no children for the females.

** The other characteristics assumed for this hypothetical group are: no children and no failed marriage (for women), secondary school graduation and duration of 2 years in state they are leaving. If other characteristics had been selected, the absolute values of probabilities would have changed, but the relative values of married and unmarried would stay approximately the same.

For males, the finding was the opposite, although the effect of marital status seemed to be weaker.[6] The probabilities of first entering a job are from 1.0 to 1.4 times higher for married than unmarried men. The probabilities of leaving and re-entering employment are no different, or only slightly different between married and unmarried men. Thus, the effect of marital status seems to be of significance only in the first entry equations for men; the strength of the marital status effect seems to be much weaker than among women.

Education

Years of formal education is one of the most important variables determining wage levels.[7] In the context of this project, one would expect that higher levels of education would increase the probability of entering or re-entering employment and decrease the probability of leaving it, given that all other factors remain unchanged.

There are a number of reasons why one would expect such a relationship. For example, the education variable may serve to some extent as a proxy for individuals underlying preferences for labour market-oriented versus home-oriented activities. Those whose tastes are oriented towards the former might seek a higher level of education in the belief that it would assist them in developing a career. They are also more likely to seek employment. Thus, a higher probability of being employed would be associated with higher levels of education. Secondly, it is well known that once unemployed, persons with higher levels of education are, on average, re-employed more quickly than their less educated counterparts. Thus, to the extent that the non-employment spells observed here are involuntary unemployment spells, one would expect the probability of re-employment to be higher (in any given year) for the more highly educated. Also, the potential of earning a higher wage should tend to increase the probability of entering employment and decrease the probability of leaving it for the more highly educated; their opportunity costs of not working are higher than for the less educated.

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[6] Recall that employed in this paper means employed at any time during the year. The duration of employment within a year is not accounted for. Thus, these regression results likely underestimate the difference between married and unmarried women in the total amount of labour supplied over some period, since married women likely work less during a given year (i.e. more part-time employment) than unmarried women.

[7] For example, see Smith (ed., 1980), Heckman (1974), Nakamura and Nakamura (1981, 1983).

The coefficient estimates for the education variables are shown in Tables 1 to 4. As expected, the higher the level of education, the less likely a man or woman is to leave employment and the more likely they are to re-enter it, after controlling for other factors (marital status, child status, duration in the state). The probabilities calculated for a hypothetical population in Table 6 indicates that the elementary educated in the 20-39 group are 1.5 times as likely to leave employment and only half as likely to re-enter it as their counterparts with postsecondary education. Note, however, that all the E to NE transition probabilities are quite small for males, so in an absolute sense the education variable has little real effect on this transition probability for males , even though the reqression coefficients appear to be large in some cases. Thus, the education effect is more significant for women than men. This may be because most not employed spells for men are likely unemployment spells, and higher levels of education are associated with shorter spells of unemployment. For women, the not employed spells may be related to family related duties as well as unemployment.

TABLE 8: Estimated Probability of Making a Transition by Educational Attainment (Estimates Based on Logistic Regressions)

Transition Type and Hypothetical Population Group	Elem.	Some Secondary	Completed Secondary	Completed Postsec.
Prob. of Leaving Employment Given Have Been in E for 2 Yrs.** PR (E to NE | in E 2 Yrs.)				
Male Age 20-39	.03	.04	.03	.02
40-50	.03	.02	.03	.02
Female Age 20-39	.19	.20	.15	.14
40-50	.08	.07	.06	.05
Prob. of Re-entering Employment Given Have Been in NE for 2 Yrs.** PR (NE to E | in NE 2 Yrs.)				
Male Age 20-39	.12	.16	.16	.31
40-50	.09	.04	.10	.14
Female Age 20-39	.07	.10	.12	.17
40-50	.05	.07	.12	.12

* Other characteristics of this hypothetical group are not married and no children.

** Other characteristics are married, no children, no failed marriage, completed secondary school.

Child Status Variables

That the presence or absence of children affects the employment patterns of women is commonly known. It is important to realize, however, the exact question which is being addressed in this model. The question addressed is not "does having children influence the probability of being employed (or not employed)?", but rather "given that a person is already employed (or not employed), will having children influence the probability of changing their employment status?"

Having a newborn (child aged 0) would be expected to influence the probability that an employed woman will leave employment, or that a woman who is not employed will enter employment. This event represents a significant change between two years in family status, and in the non-work related burdens and responsibilities of the family. However, whether having children in the, say, 1 to 6 age group will influence these probabilities is a different question. In this case, no major change is observed in family status from one year to the next, and the woman's preference for work or non-work related activities is likely already reflected in the employment status of the previous year. But do women with preschoolers (excluding newborns) who have chosen to work display a stronger or weaker attachment to employment than their counterparts without children? This question is addressed here.

The logistic coefficients in seven models which employ child status variables are shown in Tables 1 to 4. The estimated probabilities of changing employment states given various child status conditions is shown for selected hypothetical populations in Table 9. Together, one can draw the following conclusions from these two tables:

(1) Women with preschoolers (less than 6 years old) are approximately one-half as likely to enter employment for the first time in any given year as their counterparts with older children or no children (having controlled for age, marital status).

(2) Women with newborns have a higher probability of leaving employment than those with no children, (by a factor of from 1.4 to 2), but those with children aged 1 to 16 are less likely (by a factor of about half) to

TABLE 9: Estimated Probability of Making a Transition, by Child Status, Females Only (Estimates Based on Logistic Regression)

Transition Type and Hypothetical Population Group	Child 0-5		Child Over 6 or No Children	
Prob. of First Entering Employment Given Never Worked and Left School With Education Level Specified				
Elem. of Some Sec./Age 18	.10		.19	
Sec. School Grad./Age 18	.12		.24	
Postsec. Grad./Age 24	.19		.40	
	Child 0	Child 1-5	Child 6-16	No Childr Under 17
Prob. of Leaving Employment Given Have Been in E for 2 Years*				
PR (E to NE | in E 2 Yrs.)				
Age 15-19	.17	.17	.13	.13
Age 20-39	.23	.09	.07	.15
Prob. of Re-entering Employment Given Been in the NE State 2 Years*				
PR (NE to E | in NE 2 Yrs.)				
Age 15-19	.13	.13	.09	.09
Age 20-39	.07	.13	.08	.12

* Other characteristics of this hypothetical group are married, completed secondary school, and no fa marriage.

leave employment (once employed) than their counterparts without children, controlling for marital status, duration in employment and educational attainment.

(3) The patterns for the probabilities of re-entering employment are the mirror image of these for the probability of leaving. Women with newborns have a lower probability of re-entering than their counterparts without children, and most women (in the 20-39 age group) with children aged 1 to 16 have a slightly higher probability of re-entering (by a factor of around 1.2) than women without children.

A few comments about these observations. It must be remembered that only spells of non-employment lasting 1 year or more are included in these data. Shorter spells away from employment are not picked up in these data, and many women with newborns now return to work after a few months. Hence, what is observed here is a major shift in employment status. Second, the observation that women with children (other than newborns) who have chosen to work are even less likely to leave it than their counterparts without children is most interesting. This may be related to financial need. Women with children who work may often do so because of financial pressures. If such pressures did not exist they would perhaps be more likely to stay in the home than their counterparts without children simply because of the presence of the children. Thus, once employed, they may feel a stronger need to remain so than other women. But this is speculation, without any support from these data. There are other possibilities. No distinction is made here between part-time and full-time employment, and it is likely that the former plays a larger role among women with children than among those without. Entry and exit probabilities may be different for part-time and full-time employment, and perhaps it is this difference which is being observed. This particular finding should be considered preliminary until other evidence can be brought to bear.

The Employment Population Ratio

The employment population ratio (EPR) is simply the ratio of the number of persons employed within a given demographic group divided by the population

in the same group.[8] This variable, expressed as $(EPR_t/EPR_{t-1}) - 1$, is included because in the pension simulation model for which these sub-models are being developed, it is desirable to be able to simulate alternative pension scenarios under varying assumptions regarding the employment/population ratio, particularly for women. To do this, the transition probabilities must be made to alter with assumed changes in the employment/population ratios such that the simulation in fact produces the desired levels of employment. This can be done either by introducing the employment/population ratio into the model (as is attempted here), or by "scaling" (adjusting) the transition probabilities in some way until the desired employment/population ratio is achieved.

Different values of the employment/population ratios were introduced in the model for 4 age groups for men, 8 age/child status groups for women, and the 10 years from 1974 to 1983 inclusive. The model coefficients are shown in Tables 1 to 4. All the signs are as one would expect; when the employment population increases, the NE to E transition probabilities rise the NE to E probabilities fall. The converse is true when the employment population falls. However, the magnitude of the coefficients are such that the inclusion of the employment/population ratio in the model is not a satisfactory way of making the transition probability "track" and assumed changes in the external employment population ratio. Thus, this variable will not be used in the model for that purpose.

Comparison of the Actual and Simulated Employment Patterns

To assess the reasonableness of the modelled transition probabilities, a comparison is made between the actual and simulated patterns of employment. A Monte Carlo method is used to develop lifetime employment patterns for a hypothetical population of 2000 cases. The lifetime employment patterns of men and women - where employed is defined as being employed at any time during the year - are developed in a number of steps. All individuals start at age 15 in the not employed (NE) state, and each year either remain in the state or are moved to their first employment. This is done by estimating the probability of employment using the "probability of first employment" equation, and a

[8] The employment population ratio used here does not conceptually match that reported by the Labour Force Survey (LFS), since "employed" in this work refers to employed at any time during the year. In the LFS ratios, the amount of employment during a year is accounted for.

monte carlo random draw procedure. Once in the employed (E) state, each year the probability of exiting from the state is determined by "probability of E to NE transition" equation[9], and a Monte Carlo method is applied to determine if the individual actually makes the transition. Similarly, when in the NE state a "probability of NE to E transition" equation is used to generate the probability of a transition, and the Monte Carlo method to determine when individuals move from NE to E. In this way the lifetime employment is simulated based on the transition probabilities equation and a monte carlo method. The information on marital status, age, educational attainment, and child status necessary to estimate the transition probabilities for this hypothetical population is generated for each case in earlier sub-models of the overall LIPPS model.

From the hypothetical population, ten year segments of the lifetime employment patterns were selected to compare to the actual 10 year segments (from 1974 to 1983) in the FHS used to estimate the transition models. A number of statistics were then computed for 4 age/sex groups to compare the patterns in the hypothetical and actual population. The results are in Table 10.

Overall, the simulations seem to fairly reliably reproduce the actual data. The one exception appears to older women, where the simulation models appear to be generating too many employment spells and overall, too much employment.[10]

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9 In this test, the employment population ratio was assumed to remain constant (i.e. the variable in the equations had a value 0).

10 This particular test may not be totally appropriate, since the model is estimated using data from one period (1974 to 1983), and is then used to generate employment spells which are compared to "actual" spells which are influenced by the events of the period from, say 1950 to 1983. This is particularly true when comparing spells for the older population. Employment in the older years in the model is influenced by employment patterns in an individual's younger years because it is essentially a "flow" model. For people in the, say, 37 to 55 age group, their "actual" employment patterns in their youth reflected the relationships evident in the, say, 1945 to 1965 period. But in the model-generated employment patterns, their patterns for their youth reflect the relationships of the 1974-83 period, which are quite different. Thus, the model may over-predict employment in peoples older years (which in fact it does), mainly because it over-predicts employment in their younger years, which in turn influences employment patterns in later age groups. To implement a better test, one could start with the "actual" employment patterns of, say, 37 year olds and use the model to predict their employment patterns from that age on, rather than using the "predicted" employment patterns of 37 years old as a starting point.

TABLE 10: Comparison of the Actual and Simulated Employment Spells, by Sex and Age Group

Test Statistic		MALES: Age at Start of 10 Yr. Period* 18-36	MALES: Age at Start of 10 Yr. Period* 37-55	FEMALES: Age at Start of 10 Yr. Period 18-36	FEMALES: Age at Start of 10 Yr. Period 37-55
<u>During 10 Year Period</u>:					
Average # Years Employed:	Actual	8.8	8.9	4.7	3.6
	Simulated	8.4	7.9	5.4	5.7
Number of NE to E Transitions per 100 People:	Actual	27	2	44	12
	Simulated	24	4	42	14
Number of E to NE Transitions per 100 People:	Actual	9	17	29	16
	Simulated	15	15	33	24
Average Duration of Employed Spells:	Actual	8.7	9.4	6.1	7.8
	Simulated	8.6	9.1	6.5	7.9
Average Duration of Not Employed Spells:	Actual	4.2	4.7	6.4	8.3
	Simulated	4.4	6.7	5.8	7.0
Average Number of Employed Spells per 100 people	Actual	105	96	84	48
	Simulated	101	87	91	75

The actual employment pattern during the period 1974 to 1983 of 500 randomly selected cases within each of the 4 age/sex groups (total sample of 2000) were compared with a similarly selected and equal number of observations from the simulated population. Ten year segments of the simulated lifetime employment histories were selected for comparison with the actual FHS data for 1974 to 1983.

CONCLUSIONS

This work focused on movement in and out of employment over the period 1974 to 1983. As expected, a larger proportion of women than men registered no employment during the period, and women who did work experienced more movement in and out of employment. Approximately 17% of the younger women (aged 18 to 36 at the beginning of the period) and 44% of older women (aged 37 to 55) were not employed at any time during the 10 years, compared with approximately 2% of men in both age groups. And women who did work were more likely

to have interruptions; approximately three-quarters of all men worked continuously over the 10 year period, compared to only one-third of the women. But there did not seem to be a rapid succession of employment/non-employment spells among women. Even among younger women - where one would expect considerable movement between employment and non-employment - only about 16% registered two or more employment spells during the 10 years, compared to 8% for younger men. Thus, while women make more transitions (approximately twice as many on average as men), it is not a case of a rapid succession of in-out movements. In this work, these employment patterns are reflected in generally higher probabilities of exiting employment and lower probabilities of first entering or re-entering for women than men, although these vary according to the individual's characteristics.

Marital status, educational attainment, the employment state occupied the previous year, the number of years employed (or not employed), and the presence of a newborn all significantly influenced the probabilities of entering or leaving employment for women. Once the current employment status is controlled for, the existence of children (other than newborns) did not radically affect the probability of changing employment states. If anything, the existence of children decreased the probability of leaving employment in any given year.

Implications for Data Sources

Ideally, one would have true longitudinal panel data to estimate model parameters and examine the issue of female labour supply. This is not likely in the near future in Canada. However, if the sample were large (e.g., a supplement to the labour force survey), a cross-sectional survey with recall data for the previous year would suffice in most cases. The major gap in the FHS data is the lack of wage and income data, and more detailed information on hours of work, or the part-time/full-time nature of employment. Nakamura and Nakamura (1985) found that when the model controls for the current employment state (as this one does), spouses income, other family income and previous year's wages appear to have only a weak influence on the transition probabilities. Hence, excluding these variables from this model may not be a serious omission. Nonetheless, the relationship between income and employment pat-

terns probably should receive more attention. As well, it has been found here that duration in the state is a very important variable. If, as is suggested here, the "experience" variable is included in the form of number of years in the state, this could be captured through recall on a cross-sectional survey. Such a survey would collect information on family and demographic variables, income variables and employment variables for the current year, as well as information on any changes in these variables between the current and previous year, and the length of time in the employment state occupied the previous year. It should be stressed, however, that a general purpose labour force longitudinal survey would be the favoured approach, since it would provide not only more reliable data for work on the labour supply of women, but for numerous other issues as well.

BIBLIOGRAPHY

Allison, Paul D., Discrete-Time Methods for the Analysis of Event Histories, in Sociological Methodology, S. Leinhadt (ed.), 1982.

Amemiya, T., Qualitative Response Models: A Survey, Journal of Economic Literature, Vol. XIX, December 1981, pg. 1483-1536.

Becker, G.S., Human Capital: A Theoretical and Empirical Analysis, National Bureau of Economic Research, New York: Columbia University Press, 1954.

Becker, G.S., A Theory of the Allocation of Time, The Economic Journal, 75:299, September 1965, 493-517.

Boothby, Daniel, The Continuity of Married Women's Labour Force Participation in Canada, Canadian Journal of Economics, XVII, No. 3, August 1984.

Bowen, W.G. and Finnegan, T.A., The Economics of Labour Force Participation, Princeton N.J., Princeton University Press, 1969.

Cain, G.C., Married Women in the Labour Force, University of Chicago Press, 1966.

Goldberger, A.S., "Linear Regression after Selection", Journal of Econometrics, 1981, 357-366.

Groneau, R., Wage Comparisons - A Selectivity Bias, Journal of Political Economy, 82, 1974, 1119-1143.

Hanoch, G., A Multivariate Model of Labour Supply, Methodology and Estimating in Female Labour Supply, Smith (Ed.0, 1980.

Hasan, A. and de Broucker, P., Unemployment and Non-Participatin in Canadian Labour Markets, Economic Council of Canada, Ottawa, 1985.

Heckman, J.J., A Partial Survey of Recent Research on the Labour Supply of Women, American Economic Review, 1978, 200-207.

Heckman, J.J., The Sample Selection Bias as a Specification Error with an Application to the Estimation of Labour Supply Functions, in J.P. Smith (Ed.) Female Labour Supply: Theory and Estimates, Princeton University Press, 1980, 206-248.

Heckman, J.J., The Common Structure of Statistical Models of Transition, Sample Selection and Limited Dependent Variables and a Simple Estimation for Such Models, Journal of Economic and Social Measurement, 1976, 200-207.

Jackson, B.B., Multivariate Data Analysis, Richard D. Irwin, Homewood Illinois, 1983.

Mincer, Jacob, "Labour Force Participation of Married Women", in Aspects of Labour Economics, H.G. Lewis (Ed.), National Bureau of Economic Research, Princeton, N.J., Princeton University Press, 1962, 63-105.

Nakamura, A. and Nakamura M., The Second Paycheck, Academic Press Inc., 1985.

Nakamura, A. and Nakamura, M., "Part-Time and Full-Time Work Behaviour of Married Women: A Model with Douby Truncated Dependent Variable", Canadian Journal of Economics, 1983, 229-257.

Schultz, T.P., "The Influence of Fertility on Labour Supply of Married Women: Simultaneous Equations Estimates", Research in Labour Economics, 1978, 273-351.

Schultz, T.P., Estimating Labour Supply Functions for Married Women, in J.P. Smith (Ed.), Female Labour Supply: Theory and Estimation, Princeton University, 1980, 25-89.

Smith, J.P. (Ed.), Female Labour Supply, Princeton University Press, 1980.

Stopher, P.R. and Meyburg, A.H., Survey Sampling and Multivariate Analysis for Social Scientists and Engineers, Lexington Books, 1979.

Wolfson, M., DEMOGEN and the Impact of Divorce on Family Life Histories, paper presented in "Family in Crisis" seminar, University of Ottawa, November 1986.

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